What Shall We Do With The Data We Are Expecting from Upcoming Earth Observation Satellites?

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Abstract

The community of researchers studying global climate change is preparing to launch the first Earth Observing System (EOS) satellite, EOS AM-1. The satellite will generate huge amounts of data, filling gaps in the information available to address critical questions about Earth's climate. But many data handling and **data analysis** problems must be solved if we are to make best use of the new measurements. In key areas, the experience and expertise of the statistics community could be of great help.

statistics level 2 data

1. Introduction

level 1 data
remote sensing data

The first Earth Observing System (EOS) platform, EOS AM-1, is scheduled for launch into polar orbit in 1999. It will carry five remote sensing instruments designed to study the surface and atmosphere of Earth. In a broad sense, the purpose of these observations is to find indications of how Earth's climate is changing, and to discover clues to the mechanisms that are responsible for these changes. A 5 to 15 year program of global monitoring is planned, involving measurements at many wavelengths, with spatial resolutions as small as 0.25 km and temporal coverage as frequent as daily. Higher resolution data on regional scales will also be acquired.

The surface area of Earth is about 5 x 10^8 km^2. At 0.25 km resolution, a single instrument acquiring 36 channels of data, such as the Multi-angle Imaging SpectroRadiometer (MISR) [*Diner et al., 1998*] or the Moderate Resolution Imaging Spectrometer (MODIS) [*King, et al., 1992*] on the EOS AM-1 satellite, will generate upwards of 80 Gbyte/day, or 30 Tbyte/year, of basic data. The geophysical quantities are generally retrieved at lower spatial resolution, but must include quality flags and other ancillary information, resulting in a geophysical data set that will be no smaller than 3 Tbyte/year for the MISR instrument alone.

The sheer volume of data creates unprecedented challenges for accomplishing basic data handling operations, such as throughput and storage. But there are deeper issues regarding the scientific use of such large data sets. The EOS community has adopted a partial framework, and some terminology, for discussing the questions we must face. However, current approaches rely heavily upon the traditional ways remote sensing satellite data have been analyzed, which make little use of modern statistical techniques.

This paper begins with a brief review of the data classification scheme we use to organize our thinking about data handling and analysis. This is followed by descriptions of the current approaches to each of the key scientific analysis steps for EOS-type data, highlighting some of the outstanding statistical issues. The paper concludes with a summary of those issues to which the statistics community may be well equipped to contribute.

2. Data Classification Scheme

The Committee on Data Management And Computing define five general classes of spacecraft data, based on the degree of processing involved [*CODMAC, 1982*, and subsequent refinements]:

- **Level 0** -- The raw data stream from the spacecraft, as received at Earth

- **Level 1** -- Measured radiances, geometrically and radiometrically calibrated
- **Level 2** -- Geophysical parameters, at the highest resolution available
- **Level 3** -- Averaged data, providing spatially and temporally "uniform" coverage
- **Level 4** -- Data produced by a theoretical model, possibly with measurements as inputs

This paper focuses on Level 2 and Level 3 data, which are the main concerns of most global change research scientists working on EOS instrument teams. Level 2 products are reported on an orbit-by-orbit basis. For a polar-orbiting satellite such as EOS AM-1, the Level 2 sampling of Earth is highly non-uniform in space and time, with coverage at high latitudes much more frequent than near the equator. Level 2 data are needed when accuracy at high spatial resolution is more important than uniformity of coverage. These situations arise routinely for validation studies of the satellite observations, in the analysis of field campaign data, and when addressing other local- and regional-scale problems with satellite data.

The spatially and temporally uniform Level 3 data are needed for global-scale budget calculations, and for any problem that involves deriving new quantities from two or more measurements which have different sampling characteristics. The transition from Level 2 to Level 3 data usually involves a substantial reduction in data volume, which is another reason many researchers prefer to work with Level 3 data when it is adequate to their needs. Level 3 data sets can also be useful as guides to the structure of the Level 2 data, helping identify portions of it for further detailed investigation. To derive a Level 3 product from Level 2 data, scales for spatial and temporal sampling must be chosen. We begin by discussing Level 2 data processing, with emphasis on statistical issues.

3. Level 2 Data

The generation of Level 2 geophysical quantities from calibrated reflectances introduces a diverse set of issues, since the algorithms used to derive these quantities vary greatly with the type of measurement made and the retrieval strategy adopted. For specificity, we use the MISR aerosol retrieval process [*Martonchik et al., 1998*] as the basis for the discussion in this section.

Aerosols are micron-sized particles suspended in the atmosphere, whose light scattering properties are determined primarily by the particle size distribution (parameterized by an effective particle radius), composition (represented by the real and imaginary parts of the particle index of refraction), and amount -- a total of 4 quantities. (In general, the parameter space also includes mixes of particle size distributions and compositions, atmospheric relative humidity, and surface type.) The retrieval algorithm aims to determine these 4 properties from satellite measurements of brightness taken at 9 angles and 4 wavelengths (a total of 36 radiance measurements per geographic location).

Since this is a highly underdetermined problem, our approach is to simulate the reflectances that would be measured for a range of climatologically likely aerosol types and amounts, and to classify the actual observations by comparing them with each of the simulated cases. This amounts to comparing observed with climatologically "expected" values, which we do using a series of chi-squared-like quantities.

Two MISR-related issues similar to ones that arise elsewhere are: (1) How to determine the sensitivity of the instrument to differences in atmospheric aerosol properties, a part of the process of designing the retrieval itself, and (2) How to create spatial and temporal summaries of the retrieved geophysical quantities (what we call "climatologies") based on data from other sources, to be used to validate the Level 2 retrieval results.

3.1. Sensitivity Studies

Sensitivity studies are done to help determine how fine a grid of simulated aerosol properties is appropriate to use in the retrieval. This amounts to asking: " "Into how many groups can we divide the MISR observations based on the 4 aerosol properties of interest (particle size, composition, etc.)?". We can divide data sets having greater "information content" into larger numbers of groups.

The sensitivity analysis we are doing for MISR is summarized by *Kahn et al.* [*1997; 1998*]. We run simulations using a theoretical model, calculating reflectances at the 4 wavelengths and 9 viewing angles covered by the MISR instrument for a wide range of aerosol size distributions, compositions, and amounts. For the purpose of the sensitivity study, these simulations provide data for both the "observed" measurements and the "expected" reflectances of the comparison models.

We designate the one set of simulated reflectances as the "measured" (observed) case, and step through "expected" (comparison) models covering a range of alternative size distributions, compositions, and amounts. We define 4 test variables to make the comparisons; for each test, the largest of the 4 test variables determines the outcome. One test variable is called χ^2_{abs}:

$$\chi^2_{abs} = \frac{1}{N\bar{w}} \sum_{l=1}^{4} \sum_{k=1}^{9} \frac{w_k \left[\rho_{meas}(l,k) - \rho_{comp}(l,k) \right]^2}{\sigma^2_{abs}(l,k)} \tag{1}$$

where ρ_{meas} is the simulated "measurement" of atmospheric equivalent reflectance and ρ_{comp} is the simulated equivalent reflectance for the comparison model. The subscripts l and k index wavelength band and camera, N is the number of measurements included in the calculation, w_k are weights, chosen to be proportional to the amount of atmosphere seen by each camera k, $\bar{w}$ is the average of weights for all the measurements included in the summation. σ_{abs} is the absolute calibration uncertainty in the equivalent reflectance for MISR band l and camera k.

Comparisons made using χ^2_{abs} reduce the information contained in as many as 36 individual measurements (4 wavelengths x 9 angles) to a single number. There is more information in the data. Another two ways to compare cases, that use other information in the reflectances, are:

$$\chi^2_{\max dev} = \underset{l,k}{Max} \frac{\left[\rho_{meas}(l,k) - \rho_{comp}(l,k) \right]^2}{\sigma^2_{abs}(l,k)} \tag{2}$$

which is the maximum deviation of all the measurements used, and a test variable normalized to the measurements at the nadir (downward looking) angle:

$$\chi^2_{geom} = \frac{1}{N\bar{w}} \sum_{l=1}^{4} \sum_{\substack{k=1 \\ k \neq nadir}}^{9} \frac{w_k \left[\frac{\rho_{meas}(l,k)}{\rho_{meas}(l,nadir)} - \frac{\rho_{comp}(l,k)}{\rho_{comp}(l,nadir)} \right]^2}{\sigma^2_{geom}(l,k)} \tag{3}$$

Here σ^2_{geom} (a dimensionless quantity) is the uncertainty in the camera-to-camera equivalent reflectance ratio:

$$\sigma^2_{geom}(l,k) = \frac{\sigma^2_{cam}(l,k)}{\rho^2_{meas}(l,nadir)} + \frac{\sigma^2_{cam}(l,nadir)\ \rho^2_{meas}(l,k)}{\rho^4_{meas}(l,nadir)} \quad (4)$$

$\sigma_{cam}(l,k)$ is the contribution of (band l, camera k) to the camera-to-camera relative calibration reflectance uncertainty. Note that σ_{cam} includes the effects of systematic calibration errors for ratios of equivalent reflectance between cameras, as well as random error due to instrument noise [*Bruegge et al., 1998*]. For most satellite instruments, including MISR, the relative calibration reflectance uncertainty is expected to be much smaller than absolute uncertainty. A fourth χ^2 test variable, χ^2_{spec}, is produced by normalizing the reflectances to one of the spectral bands.

The initial studies consider only a dark (ocean) surface, and a single type of particle (rather than a mixture). Four independent variables are needed to characterize the aerosol properties for the "measurements," and another 4 to represent the aerosol properties for the comparison models. Since 4 variables are used in comparing the measurements with the models (χ^2_{abs}, χ^2_{geom}, χ^2_{spec}, and χ^2_{maxdev}), this creates an 8-dimensional space with 4 scalar elements at each point in the domain.

Kahn et al. [*1998*] developed an interactive, graphical technique to aid our study of this high-dimensional space. Figure 1 shows several 2-dimensional slices through the space using this technique. The value of each χ^2 variable is represented by a color from a 3-segment color bar: a logarithmic segment in shades of blue for values below 1.0, another logarithmic segment in shades of red for values greater than 5.0, and a linear segment in shades of green, yellow, and orange for values between 1.0 and 5.0. The 4 χ^2 variables are each normalized, so the same scale is appropriate for evaluating tests for each of them.

In Figure 1, the box for each test is divided into 5 fields: one small box for each of the 4 χ^2 variables, and the background, which is given the color of the largest (most red) of the 4 test variables. The background indicates the overall test result, whereas the small boxes indicate which of the χ^2 variables determined that result. In blue and black areas, the largest value for all 4 test variables is less than 1, indicating that the comparison models are close to the simulated MISR measurements. Red areas indicate comparison models that are not consistent with the MISR observations. In general, "blue" regions cover the range of comparison models in 4-space that would give acceptable retrievals for a MISR observation; the larger the blue region, the poorer the constraint on aerosol properties. (One is free to choose the criterion for an "acceptable" comparison; $\chi^2 < 1$ corresponds to all shades of blue, $\chi^2 < 2$ includes some green, etc.)

We summarize the sensitivity of MISR measurements to each of the aerosol properties of interest using bar charts, as illustrated in Figure 2. This figure shows the sensitivity test results for one aerosol property, the particle size. Each bar in each panel of this figure answers the question: With all 4 aerosol properties of the atmosphere fixed, in the entire 4-dimensional space of comparison models, what is the largest (and also what is the smallest) value of comparison model particle radius that gives an acceptable match to the atmosphere? In this case, an "acceptable match" means all the χ^2 variables are less than 2. The results of this question set the upper and lower limits of each bar.

From the entire exercise, we concluded [*Kahn et al., 1998*] that the instrument is sensitive to about 3 sizes and 2 compositional types of particles (a total of 6 "groups" -- small, medium, and large; dirty and clean -- which we call the "underwear" model). The sensitivity study provides us with some notion of the "power" of our test: the ability to reject incorrect hypotheses concerning the nature of aerosol properties. It is not a true power calculation, because no distribution is imposed on the space of "observed" aerosol properties. Nevertheless, these studies provide a means of assessing the discriminatory capability of our methodology.

3.2. Climatologies and Validation Studies

The Level 2 retrieval algorithms for EOS must run in an automatic mode, rapidly processing huge amounts of data at computing facilities far from the purview of the instrument teams. As a first step in understanding the results, we plan to automatically compare them with " the expectations" -- a climatology initially based on the best data available prior to launch.

Consider the aerosol climatology we will use to validate MISR data. The quantities of interest are the aerosol column amount and the aerosol "type", which summarizes particle composition, size distribution, and shape. We need both type and amount because the effect of aerosols on the heat balance of Earth, as represented in climate models, depends upon both the aerosol amount and, for example, how dark or light the particles are relative to the underlying surface. There exist global satellite estimates of aerosol amount at 1 km resolution, over oceans only, on a weekly basis for more than seven years [*Stowe et al., 1997*]. For these observations, particle type is assumed. There are global models giving the distributions of the main types of particles, reported at spatial scales around 500 km, on a monthly basis [*Tegen et al., 1997*]. Numerous *in situ* observations have also been made, with every conceivable spatial and temporal sampling. Some observers report aerosol amount, others provide information about aerosol type, and a few include both.

How do we merge all these data into a "climatology?" Currently, we take the global satellite data set as the initial estimate of aerosol amount over ocean. We then use the global models to establish ratios of different aerosol types, on a region-by-region basis, and to fill in the aerosol amount over land (Figure 3).

We plan to use *in situ* measurements, where available, to improve the constraints placed by the global data sets. We will experiment with ways to weight the information from different data sources based on our judgment of their reliability. We must also develop an algorithm to compare the aerosol properties derived from the new satellite data with the climatology, and to assign a measure of consistency between the two.

We will find pragmatic, though not necessarily optimal, ways to address each of these issues. Our inclination is to take a more or less Bayesian approach to improving global climatologies with data from *in situ* measurements. Promising work in the area of combining data sets having different spatial resolutions has been discussed by *Gabrosek et al.* [*1998*]. An approach similar to that adopted for improving climatologies will be taken for validating the MISR aerosol products themselves, using contemporaneous field and aircraft measurements to assess the quality of the satellite-derived quantities.

4. Level 3 Data

Having reviewed how Level 2 data are currently produced and validated, we turn to the problem of creating Level 3 data. The goal of Level 3 data is to provide geophysical quantities with spatially and temporally "uniform" coverage. They usually also offer a vast reduction in data volume from typical Level 2 satellite remote sensing products. To produce a Level 3 data set, a spatial and temporal grid is chosen, and a "binning" algorithm is adopted to assign values to each grid cell based on Level 2 data.

4.1. Global Grids for Level 3 Data

The standard EOS Level 3 grid divides Earth into cells 1° latitude by 1° longitude in size [*Sellers et al., 1995*]. This "equi-angular" global grid is currently the most popular one for Level 3 products, regardless of the characteristics of the underlying Level 2 data. A degree of latitude is about 112 kilometers, so cells are sometimes sub-divided into 0.5° by 0.5° or 0.25° by 0.25° sub-cells if higher spatial resolution is desired. But a degree of longitude varies in size from about 112 kilometers near the equator to 0 at the poles, which raises several of the issues encountered when this sort of grid is used to produce global Level 3 data.

One limitation of equal angle grids is that they have singularities at the poles, causing distortions at high latitudes that are unacceptable for many types of polar-region studies. A related problem is: when such grids are subdivided to accommodate high spatial resolution data, as is often done to represent land surface properties, grid cells at the high latitude end of the region-of-interest are unacceptably small relative to those at the low latitude end. As a consequence of these limitations, it is customary to use discipline-specific grids for polar and for land surface studies. The equal-angle approach does not produce a global grid with which one can perform effective analyses on both high and low latitude data, or high and low spatial resolution data. This issue is becoming increasingly significant as we begin to collect global-scale satellite data sets with the goal of addressing global-scale questions.

For many geophysical problems, it is also desirable to have cells of equal area. Equal-area grids make it easier to calculate inventories of spatially extensive quantities, such as cloud amount, vegetation cover, or snow extent, and to quantitatively assess changes in these quantities, since each cell receives equal area weighting. An equal area grid is needed to produce spatially and temporally uniform Level 3 representations of the distribution of measured values and density of sampling, especially when many Level 2 measurements are aggregated into a single cell.

The anisotropy created by any rectangular grid, such as the commonly used equal-angle grid, presents an additional obstacle for studies that involve calculating gradients, fluxes, and other quantities calculated using finite differences [e.g., *Kahn et al., 1991*], as well as for the modeling of errors [*Cressie, 1993*]. Some neighboring cells in a rectangular grid share an edge, whereas others share only a point. There is no general rule for weighting the contributions of each type of neighbor. Only zonal (along-latitude) gradients can be calculated in a consistent way on a global scale; even in the meridional direction, the north-south cell boundaries are usually aligned only along one meridian.

Some promising alternatives to the standard equal-angle grid are currently under investigation. We are aware of studies based on triangle or hexagon subdivisions of the spherical surface or a projection thereof, that may alleviate many of these issues [*Kimerling et al., 1998*; *Carr et al., 1998*]. A considerable body of work exists that explores the characteristics of such grids [e.g., *White et al., 1992*; *1998*; *Kimerling et al., 1998*]. Much of this work focuses on tessellations of the sphere using a regular icosaherdon. Grids can be defined so that all cells have equal area, and with no singularities at the poles or elsewhere. For hexagonal grids, all neighbors share an edge, and the distance between centroids of neighbors can be nearly equal. In addition, congruently nested systems of such grids are possible, producing subdivisions with similar geometric properties as the parent grid, but representing global coverage at higher spatial resolution.

However, more work needs to be done before such grids offer practical alternatives. No single choice of grid scheme provides all of the desirable characteristics in equal measure. For example, if equal area for all cells is rigorously enforced, disparities occur in the inter-cell distances. The tradeoffs must be evaluated and optimal choices made.

Efficient algorithms for addressing and storing data at multiple levels within a grid system, as well as fast translators to and from commonly used systems such as the equal-angle, latitude-longitude grid, must be developed. Methods are needed for selecting a "native" grid size for a given data set, and for aggregating and dis-aggregating grids at various spatial resolutions. And questions must also be addressed concerning how well, in a statistical sense, (1) a Level 3 product generated on such a grid system, (2) aggregated or dis-aggregated values of the product at other spatial scales in the nested system, and (3) finite-difference quantities calculated from neighboring cells, represent the Level 2 data from which they were derived.

4.2. Level 3 "Binning" Algorithms

In addition to the variety of possible grid choices, a binning algorithm must be selected. The binning algorithm produces a summary of Level 2 data belonging to each Level 3 grid cell. It is important to recognize that this procedure is a statistical one. What we know about the Earth from the data is captured by Level 2. Level 3 is a data reduction: a version that seeks to reduce data volume while preserving important magnitudes and relationships. Currently, the most common choice for a Level 3 algorithm is to report means and standard deviations of all Level 2 data points falling into a Level 3 cell, possibly trimming outliers or measurements flagged as being of low quality. Typically, all points included in the grid cell average are given equal weight. Occasionally medians are used instead of means.

While this approach reduces data volume significantly, it also reduces information content. Aggregating over space and time in this way threatens to average out relationships existing at higher levels of spatial and temporal resolution. Also, the aggregation is usually done variable by variable, preserving no information about covariation. In short, these choices preclude use of Level 3 data for inferential purposes in all but a very restricted class of applications.

Most researchers who work with satellite data sets are interested in the geophysical properties of Earth. But carrying inferences back to the geophysical characteristics require assumptions about the relationship between Level 2 and the phenomena of which it is a sample. These relationships are sometimes well described by the physical theory employed in creating Level 2; inference requires statistical models to quantify remaining uncertainty. There is no commonly agreed-upon way to select among the possible statistical assumptions; the choice often depends upon the particular research problem, and the experience and opinions of the researchers.

With respect to making inferences about geophysical properties of Earth from Level 3 data, two levels of statistical models are needed: one to relate Level 2 to Earth (instrument sampling, etc.), and one to distill Level 2 into Level 3. Distinguishing these two steps is useful because it allows us to focus on the empirical distribution of Level 2, which can be studied with fewer restrictive assumptions, and leaves researchers free to make their own assumptions about its relationship to Earth.

Improved Level 3 data products might preserve more characteristics of the empirical distribution of the Level 2 data set than just the (marginal) means and standard deviations. Techniques of multivariate non-parametric density estimation that preserve covariance relations as well as spatial-temporal dependence may be useful. Standard methods are probably not practical for this application, because of the high data volume. One approach may be to investigate ways of creating estimates based on samples of Level 2 data. Other promising ideas may come from current work in the area of quantization and data compression [e.g., *Chou et al., 1989*].

5. Summary of Issues

This paper concentrates on matters of potential interest to the statistics community that relate to the generation of Level 2 and Level 3 data from satellite remote sensing instruments, such as the ones scheduled to fly as part of the EOS. Table 1 is a summary of the issues raised to which the statistics community may be well-equipped to contribute. For Level 3 data, the main issues are: defining an effective system of nested grids, deriving procedures for ingesting Level 2 data into the system, and developing algorithms for aggregating and translating data that is in the system. Level 2 data presents a more diverse set of issues; we focused on performing sensitivity studies and developing climatologies.

The EOS community is preparing to derive geophysical quantities from measurements that should begin appearing in 1999. All being well, we will soon face the challenges of actually studying the data, summarizing the trends, identifying and characterizing the exceptions, and exploring the implications of the results for further data acquisition, and for global climate change. We will find practical ways to implement each of the required steps for the massive data sets we anticipate. But we will do a better job if an active community of statisticians, aware of Earth scientists' needs and constraints, participates.

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TABLE 1. Summary of Issues Raised in Creating Level 2 and Level 3 Data

General Data Processing --

- Throughput, Storage, and Distribution of Massive Data Sets
- Sorting and Searching Massive Data Sets Referenced to Time and Geographic Location
- Documenting Assumptions and Constraints

Sensitivity Studies --

- Choice of Metrics to Assess the Agreement between Observed and Expected Cases
- Strategy for Exploring Cases in Multi-Dimensional Space
- Data Visualization Techniques for Analyzing and Reporting Results

Climatologies and Validation Studies --

- Approach to Combining Model-Based and Observational Constraints
- Approach to Combining Constraints having Different Spatial Scales
  (e.g., Satellite Remote Sensing, Aircraft, and *In Situ*)
- Approach to Comparing Geophysical Quantities Derived at Different Spatial Scales
  (e.g., Satellite Remote Sensing, Aircraft, and *In Situ*)
- Approach to Applying "Climatological Constraints" to Data from Satellite Retrievals

Creating Level 3 Data --

- Choice of Nested Grid System and Associated Software
- Binning Algorithm (Continuous- and Discrete-Valued Quantities)
- Measures of Certainty for Comparisons Among Level 3 Products

Studying the Observations --

- Describing Trends in the Data at all Levels
- Identifying and Characterizing Exceptions (surprises)
- Assessing and Reporting Data Quality

Figure Captions

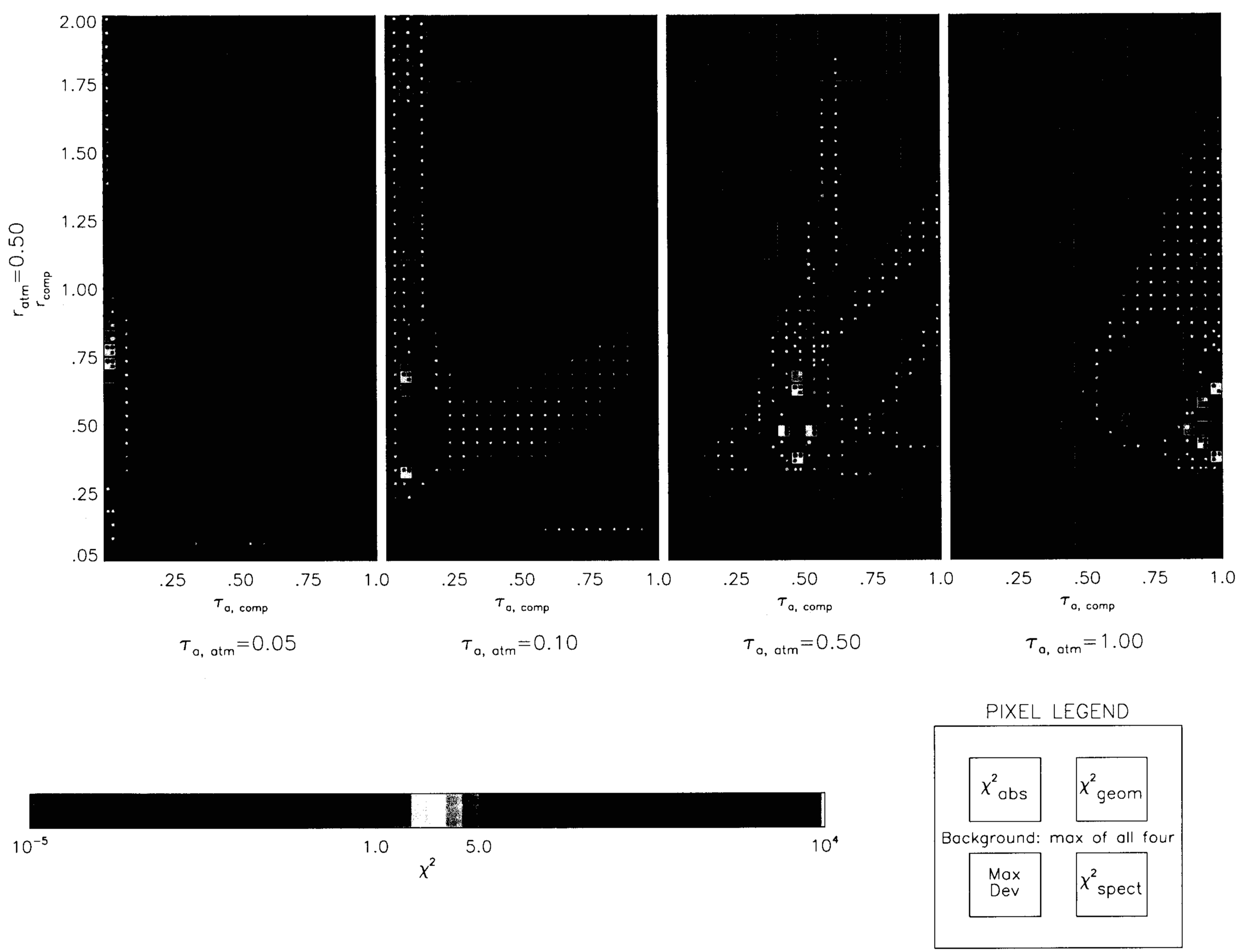
Figure 1. Example of a comparison matrix. Each panel shows the results of tests between an atmosphere containing one type of atmospheric particle (i.e., all 4 aerosol properties are fixed), and 800 comparison models, covering ranges of aerosol amount ($\tau_{a,comp}$) and size (r_{comp}). The 4 panels show tests for atmospheres with 4 different aerosol amounts ($\tau_{a,atm}$) [from *Kahn et al., 1998*].

Figure 2. Bar chart showing the ranges of particle radius (r_c) for comparison models that give acceptable matches to an atmosphere with accumulation mode particles having selected values of real and imaginary indices of refraction. For an acceptable match, all four χ^2 test variables must fall between 0 and 2. Bars are produced for 8 choices of atmospheric particle radius (r_a). For each r_a, a group of 4 bars is produced, corresponding to 4 choices of atmospheric aerosol amount (τ_a). As shading increases, the bars represent values of τ_a increasing from 0.05 to 0.1, 0.5, and 1.0. Each panel represents a different choice of atmospheric real (nr_a) and imaginary (ni_a) index of refraction [from *Kahn et al., 1998*].

Figure 3. Strategy for developing the MISR Aerosol Climatology.

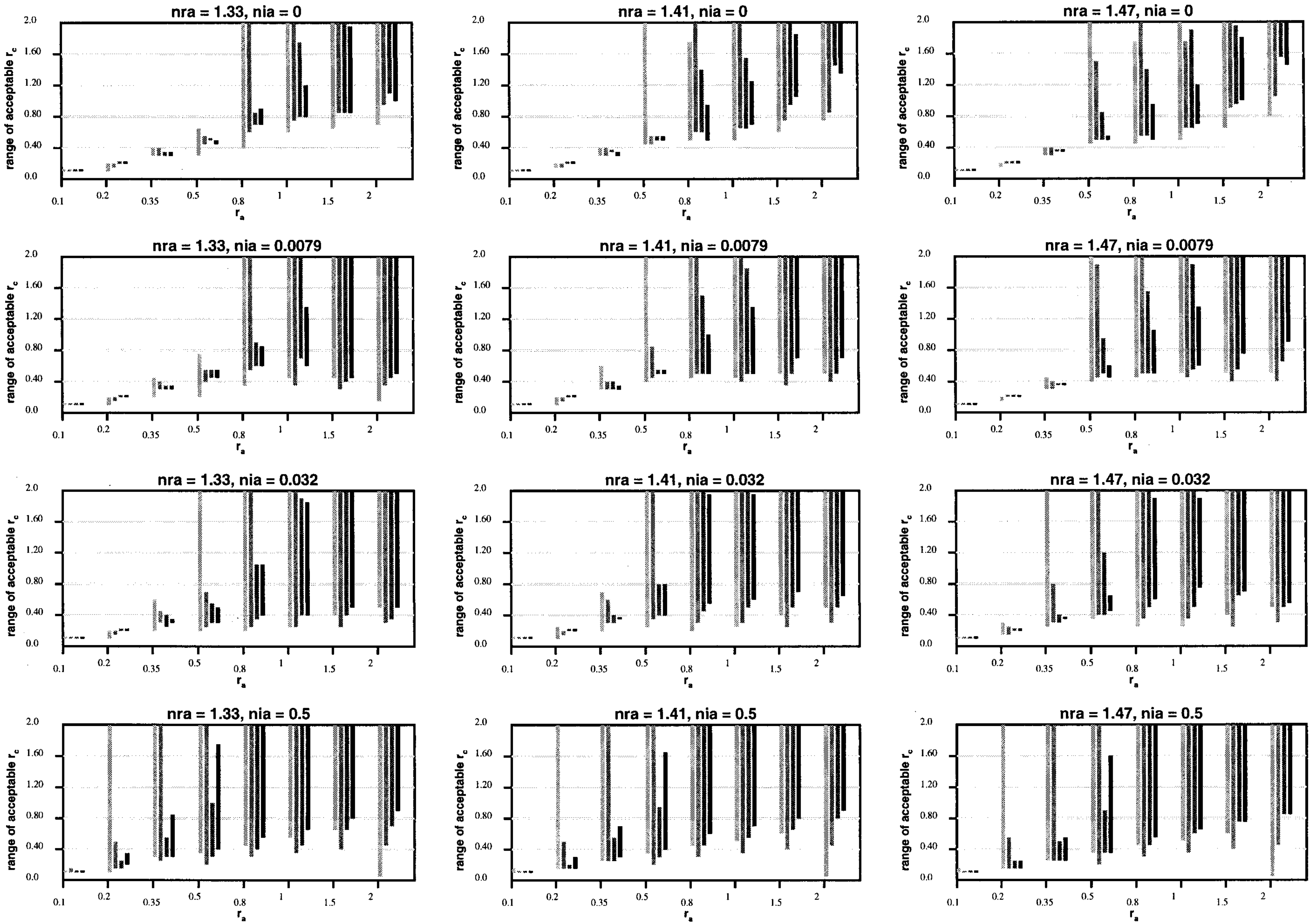
N_r 1.53 N_i 0.0 Atmosphere and Comparison (Fresnel Surface)

RH atm = 0.70 RH comp = 0.70 μ_0 = 0.60 $\Delta\phi$ = 26.0



sulfate_1_accum_rm_0.2_rh_0.70_N_vary_nr_1.53_ni_0.0000_lambda_0.670_0.865_mu0_0.60_interp.bin

Sat Dec 13 21:57:36 1997



nra = 1.33, nia = 0
nra = 1.41, nia = 0
nra = 1.47, nia = 0
nra = 1.33, nia = 0.0079
nra = 1.41, nia = 0.0079
nra = 1.47, nia = 0.0079
nra = 1.33, nia = 0.032
nra = 1.41, nia = 0.032
nra = 1.47, nia = 0.032
nra = 1.33, nia = 0.5
nra = 1.41, nia = 0.5
nra = 1.47, nia = 0.5
range of acceptable r_c
r_a
0.0
0.40
0.80
1.20
1.60
2.0
0.1
0.2
0.35
0.5
0.8
1
1.5
2

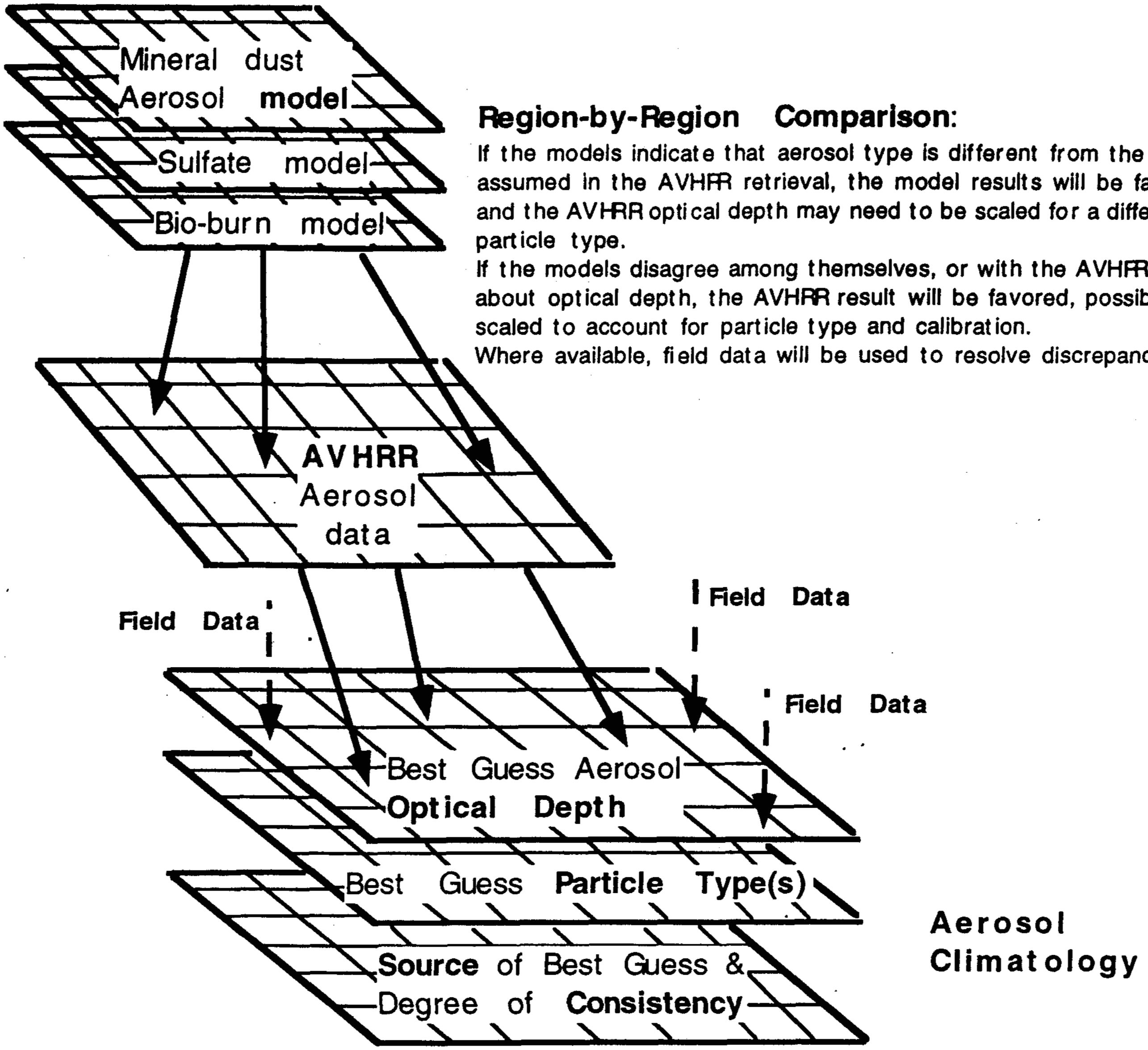


Figure 3. Application of Constraints for Tropospheric Aerosol Climatology